REMARKS

In the Office Action mailed November 29, 2001, claims 16 and 17 were objected to; claims 1-7, 10-13, 16, and 17 were rejected under 35 U.S.C. § 102(b) as being anticipated by Andersson (U.S. Patent No. 5,782,885) ("Andersson"); and claims 8, 9, 14, and 15 were rejected under 35 U.S.C. § 103(a) as being unpatentable over Spitzer et al. (U.S. Patent No. 5,092,343) ("Spitzer") in view of Andersson and further in view of Dorfmeister et al. (U.S. Patent No. 5,995,868) ("Dorfmeister"). The foregoing rejections are respectfully traversed.

The Specification and claims 1, 2, 16, and 17 are amended and claim 18 is added, and a Substitute Specification and Abstract are submitted. No new matter has been added.

Substitute Specification & Abstract:

Although not requested by the Examiner, a Substitute Specification & Abstract are concurrently submitted herewith to improve clarity, in light of the volume of changes contained in Amendment "A," which was formerly submitted. A Version With Markings To Show Changes Made indicates the changes made in Amendment "A," and a clean version indicates the status of the Specification and Abstract prior to submission of the present Amendment.

Objections to Claims 16 and 17:

In item 1 of the Office Action, claims 16 and 17 were objected to. Claims 16 and 17 have been amended, taking the Examiner's comments into consideration.

Rejections under 35 U.S.C. § 102(b):

Andersson discloses the classification of an intracardiac electrogram ("IEGM") signal of a patient using a neural network and a neural heart pacemaker, the determination of a physiological disorder or irregularity, and the treatment thereof. Andersson obtains a "predetermined number of IEGM signals" from a patient, which are then coded and stored in the neural network (Andersson, col. 2, lines 22-29). As applied to an IEGM signal to be classified (e.g., a signal derived from the heartbeat of a patient being tested), Andersson supplies the IEGM signal to the neural network, which classifies the signal *by comparing patterns in the IEGM signal with the stored reference signals* (Andersson, col. 2, lines 30-33). Based on the

classification, a stress state of the patient is determined, and the patient's heart is stimulated accordingly (Andersson, Abstract).

In contrast, claims 1, 16, and 17 of the present application (as amended herein) recite (using the language of claim 1 as an example) "predicting an abnormality of a dynamic system ... *using an information flow* that describes a development of a predictability of several future system states ... ." (emphasis added) In the present invention, the use of an information flow allows for the learning of the *dynamics* of a patient's heart, as opposed to learning just the history of the patient's heart as measured over a fixed period of time as in Andersson. By determining the dynamics of a patient's heart, it becomes possible to predict abnormalities that would otherwise go undetected while using the system disclosed in Andersson.

MPEP § 2131 states that "[a] claim is anticipated only if *each and every element* as set forth in the claim is found, either expressly or inherently described, in a single prior art reference. The *identical* invention must be shown in as complete detail as is contained in the ... claim." (emphasis added) Andersson does not describe each and every element of claims 1, 16, and 17 of the present application and thus does not anticipate the present invention. Specifically, *prediction* of abnormalities is not inherent in Andersson because Andersson only discloses diagnosis and treatment of already existing abnormalities, which are not the same as prediction. Prediction of abnormalities is inherently forward-looking, while diagnosis and treatment are inherently present and past-focused. Because of the basic difference between prediction and diagnosis/treatment, claims 1, 16, and 17 are not anticipated or rendered obvious by Andersson.

In addition to being allowable based on their dependency, either directly or indirectly, from allowable claim 1, claims 2-7 and 10-13 recite patentably distinguishing features of their own. For example, claim 2 (as amended herein) recites "wherein said processor unit endlessly loops from said determining a comparison information flow to said implementing said action."

Rejections Under 35 U.S.C. § 103(a):

Spitzer discloses detecting and analyzing physiologic waveforms using a neural network (Spitzer, col. 5, lines 50-61; col. 7, lines 50-54).

Dorfmeister discloses magnetic activation or deactivation of a nerve or region of a patient's brain (Dorfmeister, col. 6, lines 50-63).

The combination of Spitzer, Andersson, and Dorfmeister discloses detecting and analyzing physiologic waveforms using a neural network, diagnosing physiological disorders, and treating the disorders by magnetic activation or deactivation of a nerve or region of a patient's brain.

The remarks in regards to the rejections under 35 U.S.C. § 102(b) as set forth above are incorporated as if expressly set forth herein. Furthermore, MPEP § 706.02(j) sets forth the contents of a rejection under § 103: "To establish a *prima facie* case of obviousness, three basic criteria must be met. First, there must be some suggestion or motivation, either in the references themselves or in the knowledge generally available to one of ordinary skill in the art, to modify the reference or to combine reference teachings. Second, there must be a reasonable expectation of success. Finally, the prior art reference (or references when combined) must teach or suggest all the claim limitations. The teaching or suggestion to make the claimed combination and the reasonable expectation of success must both be found in the prior art and not based on applicant's disclosure." (emphasis in original) The combination of Spitzer, Andersson, and Dorfmeister does not disclose the use of an information flow, as discussed above. Therefore, claims 8, 9, 14, and 15 are allowable based on their dependency, either directly or indirectly, from allowable claim 1.

In addition, claims 8, 9, 14, and 15 recite patentably distinguishing features of their own. For example, claims 9 and 15 recite "wherein said magnetic field is supplied by at least one electrode." The combination of Spitzer, Andersson, and Dorfmeister does not disclose or suggest using an electrode to supply the magnetic field.

New claim 18:

New claim 18 patentably distinguishes over the prior art because it recites "predicting an abnormality when the information received from the system differs significantly from normal state information as determined by the neural network." Neither Andersson nor the combination of Spitzer, Andersson, and Dorfmeister discloses or suggests the prediction of an abnormality within a system. Therefore, claim 18 is allowable over the references.

In accordance with the foregoing, the Specification and claims 1, 2, 16, and 17 have been amended and claim 18 has been added. Claims 1-18 are pending and under

consideration. There being no further outstanding objections or rejections, it is submitted that the application is in condition for allowance. An early action to that effect is courteously solicited.

Finally, if there are any formal matters remaining after this response, the Examiner is requested to telephone the undersigned to attend to these matters. If there are any additional fees associated with filing of this Amendment, please charge the same to our Deposit Account No. 19-3935.

Respectfully submitted,

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CERTIFICATE UNDER 37 CFR 1.8(a)
I hereby certify that this correspondence is being deposited with the United States Postal Service as first class mail in an envelope addressed to: Commissioner of Patents and Trademarks, Washington, D.C. 20231
on 28 Feb, 2002
Freda Coleman
2/28/02

VERSION WITH MARKINGS TO SHOW CHANGES MADE

IN THE SPECIFICATION:

Please REPLACE the pending specification with the Substitute Specification attached hereto.

Please REPLACE paragraph 0011 with the following new paragraph 0011:

A goal of the invention is [a] to provide a systematic approach to the general problem, to derive a solution of this general problem from it and to determine a quantity (referred to below as prediction quantity) that is suitable for predicting dynamic events of a system. The early recognition of a pattern that represents an abnormality in a "normal" behavior of the system is of great significance, as, among other things, the following applied examples document.

IN THE CLAIMS:

Please AMEND the following claims:

1. (TWICE AMENDED) An arrangement for predicting an abnormality of a dynamic system and for implementing an action opposing the abnormality using an information flow that describes a development of a predictability of several future system states, comprising:

a) a measured data pick-up that registers comparison measured data of said system and test measured data of said system;

b) a processor unit, having a neural network that models said system, said processor unit

(1) training said neural network using said comparison measured data;

(2) determining a comparison information flow that describes a comparison dynamic of said system using said trained neural network;

(3) determining a test information flow that describes a test dynamic of said system using said test measured data;

(4) using said comparison information flow and said test information flow, predicting said abnormality as established when said comparison information flow differs significantly from said test information flow, and predicting said abnormality as not established when said comparison information flow does not significantly differ from said test information

flow;

(5) when said abnormality of the system has been predicted as established, then implementing said action; and

c) an actuator that implements said action.

2. (TWICE AMENDED) An arrangement according to claim 1, wherein said processor unit endlessly loops from said [step of] determining a comparison information flow to said [step of] implementing said action.

16. (TWICE AMENDED) A method for predicting an abnormality of a dynamic system and for implementing an action opposing the abnormality <u>using an information flow that describes a development of a predictability of several future system states</u>, comprising [the steps of]:

a) measuring comparison measured data of said system and test measured data of said system;

b) determining a neural network that models said system using said comparison measured data;

c) determining a comparison information flow that describes a comparison dynamic of said system using said neural network;

d) determining a test information flow that describes a test dynamic of said system using said test measured data;

e) comparing said comparison information flow to said test information flow using said comparison information flow and [of] said test information flow;

f) determining said abnormality to be predicted as established when said comparison information flow differs significantly from said test information flow;

g) determining said abnormality to be predicted as not established when said comparison information flows does not significantly differ from said test information flow; and

h) implementing said action when said abnormality of said system has been predicted as established.

17. (TWICE AMENDED) A method for predicting an abnormality of a dynamic system <u>using an information flow that describes a development of a predictability of several future system states</u>, comprising the steps of:

a) measuring comparison measured data of said system and test measured data of

said system;

b) determining a comparison information flow that describes a comparison dynamic of said system using said comparison measured data;

c) determining a test information flow that describes a test dynamic of said system using said test measured data;

d) comparing said comparison information flow to said test information flow using said comparison information flow and [of] said test information flow;

e) determining said abnormality to be predicted as established when said comparison information flow differs significantly from said test information flow;

f) determining said abnormality to be predicted as not established when said comparison information flow does not significantly differ from said test information flow.

Please ADD the following new claim:

18. (NEW) A method for predicting an abnormality of a dynamic system and for implementing a procedure in response to the abnormality, comprising:

training a neural network to learn the dynamics of a system;

evaluating information received from the system;

predicting an abnormality when the information received from the system differs significantly from normal state information as determined by the neural network; and

implementing a procedure, if an abnormality is predicted, to prevent or treat the abnormality.

ABSTRACT OF DISCLOSURE

[Arrangement for Predicting an Abnormality of a System and for Implementing an Action Opposing the Abnormality]

An arrangement [is] and method are presented that [enables] enable a prediction of an abnormality and [implements] implement a suitable action opposing the abnormality. An information flow underlying a dynamic system is [thereby] interpreted and a prediction quantity that comprises the abnormality as characterizing quantity of the dynamic system is determined [therefrom] from it. A neural network is trained with measured data of the system. After the training, the abnormality can be indicated on the basis of the prediction quantity before it occurs and the occurrence can be opposed with suitable measures.

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#10

Docket No.: 1454.1189

IN THE UNITED STATES PATENT AND TRADEMARK OFFICE

In re the Application of:

Gustavo DECO et al.

Serial No. 09/530,983 Group Art Unit: 3762

Confirmation No.

Filed: May 8, 2000 Examiner: OROPEZA, FRANCES P

For: ARRANGEMENT FOR PREDICTING AN ABNORMALITY OF A SYSTEM AND FOR IMPLEMENTING AN ACTION OPPOSING THE ABNORMALITY

SUBSTITUTE SPECIFICATION

VERSION WITH MARKINGS TO SHOW CHANGES MADE

COPY OF PAPERS
ORIGINALLY FILED

Attorney Docket No.: 1454.1189
Serial No.: 09/530,983

SPECIFICATION

TITLE

ARRANGEMENT FOR PREDICTING AN ABNORMALITY OF A SYSTEM AND FOR IMPLEMENTING AN ACTION OPPOSING THE ABNORMALITY

BACKGROUND OF THE INVENTION

Field of the Invention

[0001] The invention is directed to an arrangement for predicting an abnormality of a system and for the implementation of an action opposing the abnormality.

Description of the Related Art

[0002] The determination of an information flow of a system is known from [[1] and/or [2]] G. Deco, C. Schittenkopf and B. Schürmann, "Determining the information flow of dynamical systems from continuous probability distributions", Phys. Rev. Lett. 78, pages 2345-2348, 1997 (Deco), and C. Schittenkopf and G. Deco, "Testing non-linear Markovian hypotheses in dynamical systems", Physica D104, pages 61-74, 1997 (Schittenkopf).

[0003] The information flow described in these references characterizes a loss of information in a dynamic system and describes decaying statistical dependencies between the entire past and a point in time that lies p steps in the future as a function of p. Among other things, the utility of [the] such an information flow is [comprised therein] that a dynamic behavior of a complex system can be classified, [this leading thereto that] allowing a suitable parameterized model [is] to be found that enables a modelling of data of the complex dynamic system.

[0004] A neural network and the training of a neural network are known from [[3]] J. Herz, A. Krogh, R. Palmer, "Introduction to the Theory of neural computation", Addision-Wesly, 1991 (Herz).

SUMMARY OF THE INVENTION

[0005] The object of the invention is [comprised in specifying] to provide an arrangement that, [first,] enables a prediction of an abnormality of a system and then implements an action opposing the abnormality.

[0006] [This object is achieved according to the features of patent claim 1] This object is

achieved by an arrangement for predicting an abnormality of a dynamic system and for implementing an action opposing the abnormality, comprising:

a) a measured data pick-up that registers comparison measured data of the system and test measured data of the system;

b) a processor unit, having a neural network that models the system, the processor:

(1) training the neural network using the comparison measured data;

(2) determining a comparison information flow that describes a comparison dynamic of the system using the trained neural network;

(3) determining a test information flow that describes a test dynamic of the system using the test measured data;

(4) using the comparison information flow and of the test information flow, predicting the abnormality as established when the comparison information flow differs significantly from the test information flow and predicting the abnormality as not established when the comparison information flow does not significantly differ from the test information flow;

(5) when the abnormality of the system has been predicted as established, then implementing the action, and

c) an actuator that implements the action.

[0007] This object is also achieved by a method for predicting an abnormality of a dynamic system and for implementing an action opposing the abnormality, comprising the steps of:

a) measuring comparison measured data of the system and test measured data of the system;

b) determining a neural network that models the system using of the comparison measured data;

c) determining a comparison information flow that describes a comparison dynamic of the system using the neural network;

d) determining a test information flow that describes a test dynamic of the system using the test measured data;

e) comparing the comparison information flow to the test information flow using the comparison information flow and of the test information flow;

f) determining the abnormality to be predicted as established when the comparison information flow differs significantly from the test information flow;

g) determining the abnormality to be predicted as not established when the comparison information flow does not significantly differ from the test information flow; and

h) implementing the action when the abnormality of the system has been predicted as established.

[0008] Finally, this object is achieved by a method for predicting an abnormality of a dynamic system, comprising the steps of:

a) measuring comparison measured data of the system and test measured data of the system;

b) determining a comparison information flow that describes a comparison dynamic of the system using the comparison measured data;

c) determining a test information flow that describes a test dynamic of the system using the test measured data;

d) comparing the comparison information flow to the test information flow using the comparison information flow and of the test information flow;

e) determining the abnormality to be predicted as established when the comparison information flow differs significantly from the test information flow;

f) determining the abnormality to be predicted as not established when the comparison information flow does not significantly different from the test information flow.

[0009] An arrangement for predicting an abnormality of a system and for implementing an action opposing the abnormality is inventively recited[. A] that has a measured data pick-up [is provided therein] that determines measured data of the system. A processor [unit is configured such that] implements the following steps [are implemented]:

(1) a neural network is trained on the basis of the measured data;

(2) the information flow of the system is [employed in order] used to make a prediction about anticipated measured data;

(3) when the prediction indicates that the abnormality of the system is anticipated, the action is implemented[;].

[0010] [an] An actuator that implements the action is [thereby provided dependent] provided in the arrangement that depends on the respective application.

[0011] A goal of the invention is a to provide systematic approach to the general problem [and a solution of this general problem derived therefrom, the determination of a quantity], to derive a solution of this general problem from it and to determine a quantity (referred to below as prediction quantity) that is suitable for predicting dynamic events of a system. The early recognition of a pattern that represents an [attack on] abnormality in a "normal" behavior of the system is of great significance, as, among other things, the following applied examples document.

The applied strategy is divided into three steps:

1. The dynamically characterizing features of the system are extracted and adaptively learned (trained). The measure for learning the dynamics of the system in this dynamic learning phase should [adequately general in order] be general enough to correspond to stationary as well as non-stationary conditions. The dynamic learning phase is also used in order to demarcate a

normal condition of the system from an abnormal condition (abnormality).

2. At least one variable (prediction quantity) is determined with which the abnormality is successfully described.
3. As soon as an occurrence of the abnormality is indicated, the information of the impending abnormality is used in order to oppose the impending abnormality via an actuator whose job is to restore the dynamic system into the normal condition. [It is thereby to be taken into consideration] One also considers that the normal condition is subject to a natural modification over the course of time[, this being]; this is taken into consideration by adaption, i.e., continued training of the neural network[,] even after the learning phase.

[0012] One development [is comprised therein that the] endlessly loops through steps (2) and (3) of the processor unit [form an endless loop].

[0013] Another development of the invention is [comprised therein that] deals with the situation where the predetermined abnormality is an information flow with a dynamic value below a prescribable threshold. In this case, the action can be [comprised in] comprised of supplying the system with noise.

[0014] It is possible to deliver [the noise] this noise on the basis of a corresponding electrical field or a corresponding magnetic field. Both the electrical field as well as the magnetic field can [thereby] be supplied to the system [on the basis of] using at least one electrode.

[0015] An additional improvement [is comprised therein that] deals with a situation where the predetermined abnormality is an information flow having a dynamic value above a predetermined threshold. [Reaction thereto can be such that the system is excited with a regular signal. This can ensue] The system may be excited, in reaction, with a regular signal. This can take place on the basis of an electrical or magnetic field. The electrical field and/ or the magnetic field can be respectively supplied to the system [on the basis of] using at least one electrode.

[0016] In the framework of another development, it is also possible to utilize an electrical and a magnetic field in combination in order to oppose the abnormality.

[0017] [Developments of the invention also derive from the dependent claims] Developments of the invention are discussed below.

BRIEF DESCRIPTION OF THE DRAWINGS

[0018] Exemplary embodiments of the invention are presented in greater detail on the basis of the following Figures.

[Shown are:]

Figure 1 is a block diagram showing an arrangement for predicting an abnormality of a system and for implementing an action opposing the abnormality;

Figure 2 is a block diagram showing an actuator AKT2 [al], an active component, composed of a computer R, an interface IF, an energy store BT and two electrodes ELI and EL2;

Figure 3 is a flowchart showing steps of a method for [the] implementation on a processor unit.

DETAILED DESCRIPTION OF THE PREFERRED EMBODIMENTS

[0019] The measured data pick-up MDA registers measured data of a system S. To this end, the measured data pick up MDA is preferably arranged within the system S in order to register the measured data on site. The measured data are conducted to a processor unit PRE [and processed thereat] where they are processed. The processor unit PRE preferably comprises a neural network NN that, following training, suitably interprets further measured data registered by the measured data pick-up MDA. When there are indications that an action is to be implemented due to the measured data, an actuator AKT is initiated by the processor unit PRE to implement a predetermined action. The actuator preferably comprises at least one electrode that is directly driven by the processor unit PRE.

[0020] [Let it thereby be noted that the] The processor unit is arranged in the system S', as indicated in Figure 1 on the basis of the broken line and the appertaining designation of the system S'.

[0021] The system S preferably comprises the measured data pick-up MDA and/or the actuator AKT in order to respectively assure a direct access of the measured data pick-up MDA to the measured data and of the actuator AKT to the system.

[0022] Figure 2 shows a differently constructed actuator AKT 2. [Via the interface 201, this] This actuator AKT2 likewise receives a signal from the processor unit PRE, via the interface 201, that informs a computer R, which is part of the actuator AKT2, that a predetermined action

is to be implemented. [Further] Furthermore, an energy store BT is provided in the actuator [AKT2, this] AKT2. This energy store BT, controlled by the computer R, [applying] applies energy to the electrodes ELI and EL2 in a suitable way. The computer R of the actuator AKT2 [thereby] controls the interface IF in order to preferably determine amplitude and frequency of the energy applied to the electrodes ELI and EL2.

[0023] Figure 3 shows steps of the method implemented by the processor unit PRE.

[0024] [A neural network NN is trained in a step 301. To this end, measured data of a suitable scope are prescribed in order -- following the training -- to be able to make a statement as to whether anew measured data indicate an abnormality of the system. After the end of the training, an information flow (see [1] or [2]) is evaluated on the basis of current data in a step 302. An abnormality of the system can be indicated on the basis of this information flow before the occurrence of this abnormality. The abnormality is predicted in a step 303; an action that opposes an occurrence of the abnormality is implemented in a step 304. Subsequently, a branch is preferably made to the step 302.] A neural network NN is trained as follows. Both comparison data and test data are measured using the measured data pick-up MDA in process 302. The neural network NN is modeled based on the comparison measured data in process 304. This modeling is used to demarcate normal operation from abnormal operation, and permits a later determination of whether newly measured data indicates an abnormality in the system. After the ending of the training, information flows according to Deco or Schittenkoph are evaluated. A comparison information flow describing a comparison dynamic of the system is determined using the trained neural network NN in process 306. A test information flow describing a test dynamic of the system is determined using the test measured data in process 308. A comparison as to whether the test information flow differs significantly, according to some predetermined criteria, from the comparison information flow is performed in decision 310. If the comparison difference is significant, this is indicative of an abnormality that is predicted-- such an abnormality of the system can be indicated on the basis of this information flow before the occurrence of this abnormality. When a predicted abnormality is established, an action that opposes an occurrence of the abnormality is implemented in process 312, and a branch is made preferably to process 306. If the comparison difference is not significant, then the predicted abnormality is not established, and no action is implemented, a branch is made preferably to process 306.

[0025] Two applied examples follow, [these illustrating] that illustrate the possibilities of a

prediction of an abnormality.

Application 1: Electrocardiogram (ECG) Data

[0026] One application relates to the possible prediction of a fibrillating heart. The abnormality [is comprised therein that] occurs when the heart beats nearly chaotically.

[0027] ECG measured data are inventively employed in order to learn the dynamics of a heart of a patient (the training phase of the neural network NN). [It should thereby be noted that the] The dynamics of the heart vary greatly dependent, for example, on the time of day and the activity in which a person is engaged [at the] at a particular moment. Invariable quantities (prediction quantity) that significantly describe the dynamics of the heart of [the person] a person despite great variation [should] are nonetheless [be] determined. A variation of the prediction quantity enables the prediction of an abnormality of the heart. A control mechanism that restores the normal heart rhythm is started upon recognition of the abnormality.

[0028] The prediction quantity represents an imaging of a sudden variation of the complexity of the dynamics, and the actuator is realized in the form of an electrode that delivers small electrical pulses to the heart.

Application 2: Electroencephalogram (EEG) Data

[0029] The brain, [preferably the human brain,] (e.g., a human brain) is another dynamic system. When it is assumed that EEG measured data represent brain activity, one task is to suitably interpret the signals and potentially link predetermined measures [thereto. Thus, an] to them. An epileptic attack is characterized by a synchronous firing of a group of neurons that are arranged centered around a mid-point. This synchronism reduces the complexity of the dynamics of the brain and is indicated by EEG measured data. In contrast [thereto] to this, the normal condition, i.e., the normally working brain, represents a condition of irregularly firing neurons.

[0030] The early recognition of an epileptic attack becomes possible by determining a continued simplification of the dynamics of the brain The actuator for restoring the normal condition has the job of opposing this synchronism that is apparently responsible for the epileptic attack. This preferably occurs by applying a field, as explained in greater depth below.

[0031] [We shall turn to the] The second applied example for avoiding an epileptic [attack below for further-reaching comments] attack is presented below for more in-depth discussion.

The Dynamic Prediction Quantity

[0032] The idea is comprised is the expansion of the statistical approximation according to [[2]] Schittenkopf for detecting a Markov character in which a given empirical time row is inherent. One objective is to separate a deterministic part [form] from a stochastic part of a dynamic system is the [surround of the] area of statistical test theory in that the information flow of the system is analyzed. The statistical development of the dynamics is tested against a hierarchy of zero hypotheses that correspond to non-linear Markov processes with increasing order n. These processes are divided into a deterministic part and a stochastic part in the following way:

$$x_t=f(x_{t-1},\ldots,x_{t-n})+u \qquad (1),$$

[whereby] where u indicates an additive noise distributed according to Gauss with the variance O^2, x_t indicates a measured datum at the time t and f([...] $x_{t-1}, \ldots, x_{t-n}$) indicates a deterministic part.

[0033] The Markov process with the order n is defined by the conditioned probability densities thereof

$$p(x_t \mid x_{t-1},\ldots,\ x_{t-n}) \qquad \alpha \qquad \exp\left[-\frac{[x_t - f(x_{t-1},\ldots,\ x_{t-n})]^2}{2\sigma^2}\right] \qquad (2).$$

[0034] The deterministic part is implemented by a neural network NN that is trained according to the maximum likelihood principle [[4]] G. Deco, D. Obradovic, "An Information-Theoretic Approach to Neural Computing", Springer-Verlag, 1996, Chapter 7.2 (Obradovic) applied to the probability densities according to Equation (2). The stochastic part u is described by noise distributed according to Gauss, [whereby] where the variance o^2 is referred to a defined, mean last [[sic]] quadratic error. In other words, the zero hypotheses contain not only the order of the Markov process but also an actual deterministic structure. When a chaotic condition is present, thus, the order of the accepted zero hypothesis is the EED (effective

embedding dimension). This approach opens up a method for determining the EED, whereas temporary measured data are modelled parallel [thereto] to it.

[0035] This approach also allows a strict expansion of the concept of ED (embedding) when a chaotic condition prevails. The express determination of the deterministic part is a method for filtering the noise out of the time row.

[0036] The zero hypothesis is implemented with a method described in [[2]] Schittenkopf.

[0037] As known from [[1] and [2]] Deco and Schittenkopf, an information flow, i.e., a non-parametric criterion of a predictable development, is used as a discriminating statistic. A significance test is [thus] implemented for every point in time to be predicted, [whereby] where the zero hypothesis (i.e., a given assumption that is to be checked) is only accepted when the significance test is met for all quantities of the point in time to be predicted.

Analysis of Human Epilepsy Attacks

[0038] As described above, one application of the invention is represented by the analysis of EEG measured data in order to prevent an epileptic attack. One goal is [thereby to test] to test, in this analysis, whether a dynamic classification of the measured data for time windows of different size can be used as prediction quantities in order to predict an epileptic attack. In particular, two prediction quantities are recited:

a) The "reminder" of the underlying dynamics, i.e., the EED (see the above comments);

b) a non-parametric criterion for a predictability, defined by the integration of the information flow.

The approach presented here does not assume that the underlying dynamics are chaotic (even if they could be); rather, the emphasis lies on the time span preceding the epileptic attack in order to define a prediction quantity for the epileptic attack that is based on the dynamics of the system.

Control of the Epileptic Attack

[0039] An epileptic attack can be suppressed in that a constant electrical field is supplied to the regions that are affected by the epileptic attack (see [[5]] B. Gluckmann, E. Nell, T. Netoff, W. Ditto, M. Spano, S. Schiff, "Electric field suppression of epiletiform activity in hippocampal slices", Journal of Neurophysiology 76 pages 4202-4205, 1996 (Gluckmann).

[0040] According to an assumption that the normal condition of the brain is marked by chaotic dynamics, an epileptic attack is expressed by a drastic simplification of the dynamics in the brain. The epileptic attack is countered in that the reduction of the dynamics, i.e., the synchronicity is, as described above, opposed in that a noise is supplied to the system[, the brain in this case] (the brain in this case).

[0041] The delivery of this noise is preferably generated by applying an electrical field or a magnetic field in the immediate environment of (as close as possible to) the location of the action. Electrodes for generating an electrical field or coils for generating a magnetic field are preferably employed for this purpose. The synchronously firing neurons in the epileptic attack have their synchronicity disturbed by the electrical and/or magnetic field; a (seemingly) chaotic firing of the neurons is re-established in the brain, and the epileptic attack has thus been averted.

[0042] It is [thus] fundamentally important that a suitable reaction is carried out in response to an abnormal behavior of a dynamic system, [whereby] by the inventive system in which the abnormal behavior is detected with a prediction quantity. [Dependent of] Depending on the field of employment, this reaction [is comprised] may be, for example, [in] generating a chaotic field or in generating a regular field. This action, which is implemented by the actuator, is dependent on the respective field of employment. What the various versions of the method respectively have in common is a dynamic learning, [whereby] in which a significant abnormality is allocated to a prediction quantity and this prediction quantity enables a detection of an impending abnormality. [It is thereby expedient to] The methods then implement a suitable action with the actuator within a predetermined time interval preceding the occurrence of the abnormality (e.g., of the epileptic seizure or of the chaotically beating heart). The prediction quantity thus enables the recognition of an abnormality before, [this] the abnormality actually occurs.

[0043] Since the entire system changes over a longer time span in view of its dynamically normal property, an adaption of the originally learned dynamic system is [expedient] necessary. It is important to define the prediction quantity in that the data significantly characterizing an

abnormality are imaged from the entire dynamic system in the prediction quantity. A prediction of the abnormality can thus ensue even given a dynamic system subject to great fluctuations, for example, a heart that is subjected to [the greatest] a great variety of stresses, [whereby] and where one of these stresses does not necessarily indicate an abnormality.

[0044] The above-described method is illustrative of the principles of the present invention. Numerous modifications and adaptions thereof will be readily apparent to those skilled in this art without departing from the spirit and scope of the present invention.